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Estimating cost adjustments required to accomplish target savings in chronic disease management interventions: a simulation study

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Abstract

Chronic diseases are persistent ailments that are not preventable or curable with medication or vaccination. Many of the leading chronic conditions in industrialized societies may be related to lifestyle choices. The prevalence of these chronic conditions significantly affects the health, suffering, and longevity of patients. This paper demonstrates the utility of system dynamics as an approach to model and simulate the behavior of key cost factors in the implementation of population health management interventions. The study uses modeling and simulation as an evaluative method to identify potential savings stemming from an intervention within a well-defined population group. The model is flexible in that it allows policy-makers the ability to set saving targets that, in turn, generate knowledge about the cost structure adjustments necessary to reach these targets. The model provides useful insights into how the initial estimates of the cost of intervention, the resulting savings, and potential costs adjustments may change. The functionality of the model is demonstrated by means of scenarios implemented via sensitivity analysis.

Keywords

Chronic disease management, healthcare system, intervention modeling, system dynamics, decision support systems

1. Introduction

Chronic diseases are illnesses that are persistent and cannot be permanently cured with medication.[1] Some of the most common chronic diseases in the United States include diabetes, arthritis, chronic obstructive pulmonary disease (COPD), and congestive heart failure (CHF). Chronic diseases are the leading causes of disability and death in the United States and, therefore, extensively affect activities of daily living for many citizens.[2] Nearly half of all American adults have at least one chronic condition, and one quarter suffer from two or more chronic conditions.[3–5] It has been estimated that approximately 75% of healthcare costs in the USA stem from the management of chronic conditions.[6,7]

The World Health Organization[8] suggests the use of Innovative Care for Chronic Conditions (ICCC) as a universal framework that considers a wider perspective inclusive of health policy at the macro level and the patients and their families at the micro level. Weingarten et al.[9] view chronic disease as best managed by prospectively combining multiple interventions, such as education, appointment and medication reminders, and financial incentives. Wagner et al.[10] offer the chronic care model (CCM) as a framework to organize interventions, suggesting that intervention elements ranging from individual patient self-management to informed clinical decisions work in concert to manage the disease.

There are a substantial number of articles that quantify the economic burden of chronic diseases. Many methods have been specifically developed to determine the economic and health effects of interventions on population health.[11] One of the most prominent and widely used approaches to perform these evaluations is the cost-effectiveness analysis (CEA). CEA relates relevant costs and healthcare effects over a significant time frame.[12] However, most of these methods employ metrics that do

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not capture feedback effects of the interventions over time or second- and third-order impacts on the overall healthcare system.[13–16]

The relative cost of an intervention, though, may be conditioned by the choice of which cost elements are included in the analysis. For example, in most analyses, only related costs are considered.[17] However, unrelated future expenses stemming from other medical conditions may also be considered for inclusion in such analyses. These expenses may result from the extension of a patient's life due to the medical intervention itself.[18]

Within the health economics field in general, it remains controversial whether to include future costs for unrelated illnesses and non-medical expenditures within economic evaluations.[19] In addition, there is limited literature that addresses the time-dependent component of these methods.[20–22] From the healthcare delivery perspective, knowledge about the impact of implementing interventions that extend the life of population groups on a regional ambulatory healthcare system is imperative. For planning purposes, it is critical to know the potential level of resources required to face prospective increases in the demand when a set of interventions has been implemented.

Evaluating the efficiency and effectiveness of a chronic disease intervention is critical, since resources for implementing such initiatives are likely to be scarce. A cost–benefit analysis over time to identify the value of an intervention strategy in terms of consumed resources relative to increased health is meaningful.[23] Furthermore, the ability to quantify the magnitude of cost adjustments necessary to accomplish some level of cost savings while preserving health benefits of a deployed intervention is significant for policy-makers.

An intervention that is cost saving in the short run in the sense that it has resulted in less demand for healthcare services may actually increase healthcare utilization and costs in the long run. Thus, a mechanism that allows decision-makers to dynamically investigate the short- and long-term financial and health tradeoffs associated with adopting various population-based chronic disease management interventions over time is valuable.

The ability to set monetary and health improvement goals and understand the systemic consequences and potential adjustments necessary to accomplish these objectives is critical. Population health approaches, such as the patient-centered medical home (PCMH) (the US Agency for Healthcare Research and Quality (AHRQ) provides decision-makers and researchers with access to evidence-based resources about the medical home and its potential to transform primary care and improve the quality, safety, efficiency, and effectiveness; see http://www.pcmh.ahrq.gov), benefit from the application of these tools since it views healthcare delivery from the holistic perspective. Successful population-level management of chronic disease may require consideration of the complex interactions among medical, behavioral, social, and environmental elements. Healthcare institutions that capitalize on improving population health while maintaining their financial soundness may be able to retain their competitive edge, and thus, sustain their operations in the long run.[24,25]

A simulation model used as a tool to perform these evaluations over time provides an effective means of testing the effects of interventions on the healthcare system before implementing. Simulation is highly regarded as a competent tool in healthcare modeling, since it has the capacity to capture and process complex information.[26,27] Managers may be able to set monetary targets, for example saving levels, and select any combination of interventions.

The central objective of this study is to present a system dynamics model representing key cost factors involved in implementing a disease management intervention as well as a mechanism to evaluate cost adjustments required to accomplish saving targets. A goal-seeking simulation structure is employed to investigate the cost corrections required to obtain target savings. The model provides useful managerial insights into how the initial estimates of the cost of intervention, the cost of care, and the resulting savings may change as target savings are established. As this paper takes the policy-maker perspective, the model provides constructive insights into how the cost of interventions and potential saving depends upon the uncertainties and feedback effects.

The paper develops a theoretical simulation framework that is presented in five sections. Firstly, a brief review of the literature followed by the research question and approach are presented. Next, there is a detailed description of the model and simulation results are offered. The paper then concludes with the discussion of the results and the potential scope for future work.

2. Background and literature review

The benefits of proper chronic disease management may include a lessening of pain and suffering as well as extension of life. The management of chronic illnesses may have impact on the utilization of ambulatory healthcare services, and therefore, on the regional capacity to provide these services. Many authors claim that chronic disease management interventions lead to healthcare savings.[23] Fireman et al.[28] state that saving may be attained through the following means: (a) improving quality of health through use of medications and self-care such that future complications are prevented; (b) reducing overuse of healthcare by working with patients; and (c) productivity improvements by the method of allowing allocation of some tasks related to interventions from the physicians to other staff. These authors compare healthcare costs and quality trends for those under disease management.

Goetzel et al.[29] review cost–benefit studies in the chronic disease management context and report that savings from chronic disease management are not realized for all cases. For example, positive savings are observed for CHF, mixed results are observed for asthma, and negative results are reported for depression.[29] Most authors use mortality as a measure to quantify the impact of chronic disease management interventions. However, evidence of the effects of chronic disease management interventions on mortality is unclear for some chronic conditions.

Hämäläinen et al.,[30] Roccaforte et al.,[31] and Garcia-Lizana and Sarria-Santamera[32] report reductions in mortality among heart disease patients resulting from disease management intervention programs. Miksch et al.[33] report a reduced mortality among patients enrolled under a disease management program for diabetic conditions. Meigs et al.[34] conduct an analysis of web-based diabetes management interventions and assert the potential to reduce patient mortality. These analyses, however, do not consider future related and unrelated costs due to increased life expectancy.

Meltzer[17] asserts that, in most cases, the consideration of future costs has been generally limited to 'related' costs when studying the cost effectiveness of chronic disease management. The concept of 'related' healthcare costs refers to costs that are directly associated with the ailment. To illustrate this, Van Baal et al.[18] discuss a medical intervention in the form of a heart surgery that saves a patient's life. The future heart-related healthcare costs for that patient is a 'related' healthcare cost. However, if the same patient is treated within the medical system for diabetes after the heart surgery, then the cost of treating diabetes is unrelated. These authors claim that inclusion of unrelated costs when assessing the effectiveness of management interventions is gaining support.

We argue that it is necessary to consider future related and unrelated costs to evaluate the benefit of an intervention. Several studies do consider such costs. Chan et al.[35] utilize a Markov transition probabilities matrix to characterize the possibility that a patient will survive, be hospitalized, or die. They find that the patients under disease management have a longer lifespan and, hence, produce higher future costs to the system. Göhler et al.[36] and Miller et al.[37] conduct similar studies and report comparable results. The US Congressional Budget Office[38] has expressed concern that, while interventions are appropriate, from a budgeting perspective the chronic disease management interventions may contribute to projected increases in demand for medical services, and hence costs to the overall system, in the long run.

Investment decisions in disease management programs may be potentially cost effective, but prospectively not cost saving. Making informed decisions about the long-term projected demands for services such as ambulatory utilization requires recognition of the numerous interactions inherent in the management of chronic disease and ambulatory systems.[15] In the commercially insured US Medicare and Medicaid populations, for example, the single largest health expenditure is inpatient utilization (nearly 33% in 2005), with 13.3% of all emergency department visits associated with a hospital admission.[39] Thus, gauging emergency department visits provides a reliable indicator of prospective health and monetary gains. Decision-makers may examine population health management policies and better understand how various interventions, several of which are associated with the concepts of PCMH and population health management (PHM), dynamically interact to impact the overall health system utilization relative population health in the presence of chronic conditions. The suggested underlying model in this paper captures the essential aspects of health and cost evaluations and allows for the meaningful comparison of intervention strategies.

Continuity care decreases the likelihood of disease mismanagement in vulnerable populations with limited ambulatory healthcare access; for example, Fiscella and Williams[40] discuss health disparity based on socio-economic disparity. Diaz et al.,[15] employing system dynamics to consider and model access to ambulatory healthcare services in the US populations managed by medical homes engaged in PCMH practices, for example, have evidenced nearly 30% fewer emergency visits and 6% fewer hospitalizations, both of which contribute to direct savings for the patients and overall savings for the healthcare system.[41] Redirecting low-acuity patients from emergency departments toward PCMH practices may prove to be an appealing intervention that contributes to decongesting these departments. A system dynamics framework as proposed in this paper draws upon PCMH and PHM concepts and may have the potential to greatly enhance the ability of researchers to understand the complexities and costs inherent in chronic disease management.

System dynamics has been used to analyze the treatment and prevention of chronic conditions within the US population,[14,42] as well as quantifying (Homer et al. 2007[42]) enhanced in care delivery services.[43] This approach has been used to model the progression of particular chronic ailments, for example diabetes by Jones et al.[44] and Milstein et al.[45] The development of a system dynamics model that considers generic components of chronic disease management costs is developed by Diaz et al.[16] and Diaz and Behr.[46] Goal-seeking structures from system dynamics have been used to represent and simulate local search mechanisms that seek to quantify potential adjustments, for example Kim and Springer[47] and more recently Georgiadis and Michaloudis.[48]

Table 1 exhibits a very short sample of papers that use system dynamics and other methods and metrics to perform these types of evaluations.

Table 1. Sample of papers that use system dynamics and other methods.

Reference	Brief Description
Freeman et al.[49]	Present an evaluation of alternative health policies or treatment programs in which the numbers of quality-adjusted life years (QALYs) produced for each patient are added up to obtain an aggregate measure of program effectiveness.
Hansen and Østerdal[50]	Investigate deterministic and probabilistic models for healthcare economic evaluation while considering five different types of discounting functions.
Abellán-Perpiñán et al.[51]	Present a test of the predictive validity of various classes of economic evaluation models (i.e., linear, power, and exponential models).
Milstein et al.[52]	Use an evidence-based system dynamic simulation model. They find that expanding insurance coverage and improving healthcare quality would likely improve health status. The authors find that will raise costs and worsen health inequity.
Jansà et al.[53]	Evaluate interventions of treatment adherence in patients with multiple chronic conditions (MCC).
Iezzoni[54]	Suggest research in health services that includes: (1) considering MCCs and disabilities in comparative effectiveness research (CER) and assessing quality of care; and (2) identifying and evaluating the data needed to conduct CER, performance measure development.
Jia and Lubetkin[55]	Estimate economic health indicators for smoking and obesity for the USA.
Whitehead and Ali[56]	Analyze the impact of using the quality-adjusted life year (QALY) as a routine summary measure of health outcome for economic evaluation.
Ghaffarzadegan et al.[57]	Review the benefits of using small system dynamics models to address public policy questions.
Forsberg et al.[58]	Revise research literature on simulation modeling as support for healthcare decision making and proposed steps essential for the success of simulation projects.
Chen et al.[59]	Study the association between the number of chronic conditions and self-reported health-related quality of life (HRQOL).
Hirsch et al.[60]	Suggest interactive simulation modeling and game-based learning to support innovation in the planning process.

3. Research question and approach

A variety of chronic disease management interventions have been deployed to help patients live with their disorders. The central idea of implementing such interventions is to enhance their health conditions. In addition, these interventions might aim to achieve cost savings through a reduced healthcare utilization rate. Although the implementation of these interventions is attractive from the clinical perspective, the financial outcomes may be unknown. Many authors analyze the short-term saving impacts while disregarding future healthcare costs and their implications. The use of system dynamics simulation allows users to investigate the short- and long-term monetary and population health impacts associated with adopting various population-based chronic disease management interventions. Furthermore, it allows decision-makers to establish saving targets and investigate prospective cost adjustments to accomplish these aims.

This characterization presented in this paper provides a mechanism that allows for assessing required cost adjustments in the presence of interventions. The approach suggested in this paper involves the following: representing the flow of patients with given pre- and post-intervention profiles; representing the main cost elements that affect the implementation of intervention strategies; representing budgetary constraints that determine the ability to generate savings; and characterizing cost-effectiveness evaluation mechanisms that allow for quantifying health and cost impacts of the potential interventions to implement. The measure of cost effectiveness is critical in this context, since decisions have to be made regarding the selection of new treatments that can be offered to patients in the face of budget constraints. In such a situation, the treatments that are most cost effective become candidates for selection as they ensure the best possible utilization of available dollars.

Unlike other models presented in the literature, the model suggested in this paper allows for establishing monetary aims in terms of prospective savings to be attained. Furthermore, the model permits ascertainment of cost adjustments required to accomplish these aims, and thus, sheds light on the potential cost-related endeavors that decision-makers should engage in order to obtain such savings over time.

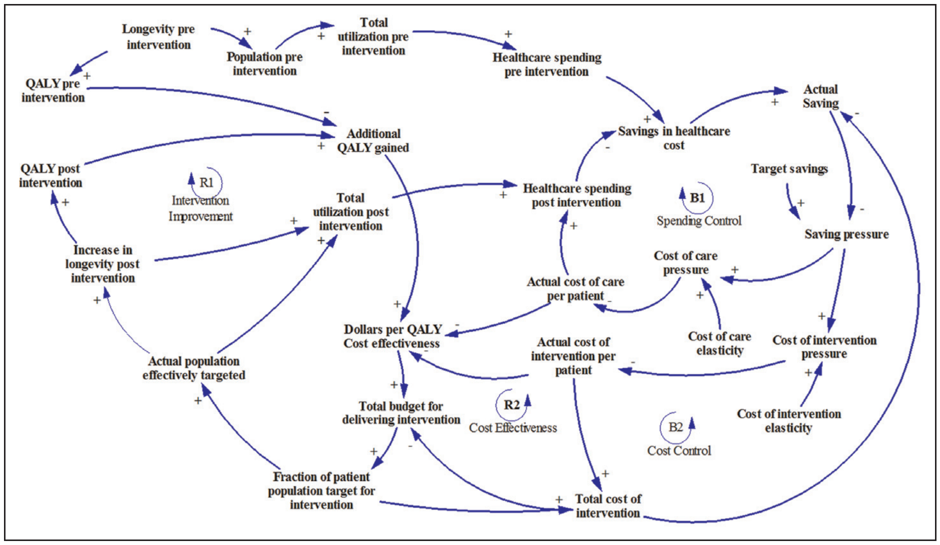

Figure 1. Causal-loop diagram for the proposed model.

4. Model description

The objective of the model is two-fold. On the one hand, the model assists policy-makers in determining how the deployment of a theoretical chronic disease management intervention may alter the utilization of healthcare services over time and, by extension, impact the overall cost to the system. On the other hand, the model includes a goal-seeking adjustment mechanism, in which cost behaviors are dynamically adjusted until a predetermined 'saving target' value is achieved and maintained through the course of the simulation. For simplification purposes, the model considers two essential cost structures: the cost of the intervention per patient and the cost of care per professional visit. The high-level causal-loop diagram that summarizes the connections among model components is illustrated in Figure 1.

The way that the model is set can be described by two co-flows that simultaneously consider the health and financial consequences given a set of initial conditions. One branch represents the behavior of the utilization of the ambulatory system in the absence of intervention, while the second branch mirrors similar dynamics in the presence of an intervention, such as the one described in Section 1. This mechanism provides an opportunity to dynamically calculate savings as the difference between the pre- and post-intervention costs. In addition, in the presence of an intervention, the model allows for setting a saving target that permits cost constraint relaxations driven by some degree of elasticity in each cost component. Co-flow and evaluating structures that consider elasticity components are extensively explained by Sterman.[61]. A detailed description of the basic model structures as well as rationales that support their inclusion follows.

4.1. Basic structures

The model considers five critical structures that relate one to another and includes populations' pre- and post-intervention, healthcare utilizations by each population group, intervention health effects, health and intervention cost components, and goal-seeking mechanisms. Since the focus of the model is on contrasting pre- and post-intervention costs while allowing for setting saving targets, the central characteristic of the model is to dynamically contrast the financial and health consequences from deployment of interventions whose target savings are set to a numerical value.

The population pre-intervention component involves three basic characteristics of the population group target. The main features that characterize these groups include their health status, mortality rates, and per capita utilization of ambulatory services. These features define the total ambulatory utilization of the pre-intervention population group over time. Likewise, the population post-intervention component assumes the same attributes that characterize the pre-intervention population in addition to other characteristics that include an aging delay and intervention target population. The age delay factors life extensions caused by a theoretical application of interventions that are assumed to extend life expectations. The intervention target population variable assumes that only one portion of the population that receives the intervention successfully experiences the benefits from the application of the theoretical intervention.

The utilization of the ambulatory system has a cost that is captured by the actual cost of care per patient and is independent of the intervention. This cost component refers to all of the direct and indirect costs that support the healthcare system in which the patient is served; for example, all of the administrative and overhead costs involved to keep the healthcare service running. An important property of this actual cost per patient is its elasticity, which reflects the degree of flexibility that can be adjusted in the presence of internal and external pressures, for example gains in efficiency and productivity as pointed out by Fireman et al.[28]. In addition to this actual utilization per capita health cost, the total post-intervention cost contains the per capita intervention cost.

The per capita intervention cost entails the expenditures associated with solely applying an intervention set to the aimed population group; for example, the cost of applying a vaccine or educating diabetic populations to measure their glucose levels at appropriate time intervals. Similar to the actual pre-intervention utilization costs, this cost has an associated elasticity that reflects the degree of flexibility that may be accomplished when external and internal forces exert pressure on the cost component, for example when administrating a vaccine may be accomplished orally in lieu of an intramuscular injection whose cost may be superior.

Actual savings are obtained by dynamically calculating the differences between post-intervention costs from the pre-intervention costs over time. Thus, the savings can be calculated for two specific situations: (1) comparing intervention effectiveness versus the absence of interventions; and (2) targeting specific savings versus the absence of interventions. The targeting specific savings scenario assumes the existence of an intervention scenario and compares savings when a target saving level is established with a situation in which target savings are absent. The general workings of the simulation model under these scenarios may be described as follows.

Both the pre- and post-intervention population stocks are initialized simultaneously. Given pre- and post-intervention conditions, both stocks lead to values of the healthcare utilization over time. As described before, the intervention population stock is influenced by health status improvements. Visits per patients and costs are employed to determine quality-adjusted life years (QALYs) and cost-effectiveness ratios that vary over time. This provides referential points that are considered when determining care and intervention costs, as well as changes in intervention budgets that influence healthcare expenditures. These influences pace the rate that savings are depleted over time. Thus, when a target saving exists, a saving pressure is generated and exerted over the cost components. Given elasticity values for each component, these cost components adjust over time, generating shifts in cost-effectiveness ratios that influence intervention budget expenditures, and thus, keeping savings to the desired level of performance.

Each cost component has an associated elasticity that reflects potential gains that can be accomplished by improving the structure cost component. In this sense, it is assumed that the cost per intervention is constrained and has limited adjusting power that can be employed to improve efficiency. Conversely, the cost of care is assumed to have a larger elasticity and allows more flexibility for improvement. The cost of care reflects systemic costs associated with delivery that encompasses many other overall costs of administration. As time progresses, the cost of care increases, and the saving obtained from applying the intervention may not be adequate to preserve the target savings. Thus, a pressure is generated to increase the efficiency in the cost of care and cost per intervention. Given the elasticity components, the cost of care and cost per intervention adjust correspondingly. These costs impact the cost-effectiveness ratio that further affects the budget per patient and can be compared to the pre-intervention and post-intervention utilization. Utilization levels determine cost contributions to savings. These savings are recurrently contrasted with the target savings and trigger the goal-seeking cost adjustment structures as previously described.

The positive loop intervention *Improvement R1* describes the overall dynamics of improvement in the patients' health, after the application of a medical intervention. This is illustrated by the Additional QALY, which is the difference between the QALY post- and pre-intervention. As health-related quality of life increases, then so does the cost per QALY gained, and ultimately the cost-effectiveness.[63] As the population grows, so does the rate of people that seeks ambulatory services. As intervention effectiveness increases the longevity post-intervention, more people might seek ambulatory services.[63] Patients could enjoy an extended life span, longer than it would otherwise be without intervention, which may potentially lead to an increase in resource utilization.[64,65]

The negative loop *Spending Control B1* presents the goal of balancing and increasing the actual savings. An increase in savings causes the savings pressure to decline. As indicated, the savings in costs is expressed by the gap between the spending pre- and post-intervention. As this target saving is not attained, the pressure to reduce total costs increases, leading to an adjustment in cost of care per patient.[66] A lower cost coupled with a high utilization rate through doctors and emergency room (ER) visits[67,68] causes the post-intervention spending to rise. This spending lowers the savings in healthcare costs while the pre-intervention spending raises it. Efforts to decrease post-intervention expenses contribute to an increase in the savings generation, which in turn reduces the savings pressure.

The negative loop *Cost Control B2* has a similar objective as the B1 loop, which is to reduce savings pressure. This loop balances the costs of intervention for patients. As the savings pressure increases, the cost of intervention per patient declines.[69] Reduction in this cost causes the total cost of intervention to mount given the growth of the fraction of patient population target for intervention.

The positive loop *Cost Effectiveness R2* represents the impact of the savings pressure on the intervention cost effectiveness. As seen in loop R1, an increase in the Dollar per QALY cost-effectiveness leads to an increase in budget, which allows for a higher number of patients to be targeted for the intervention. As the quantity of patients with improved quality of life increases, the longer life expectancy increases the total cost of care.[70] These costs are compared to the savings in healthcare in order to generate actual saving.

4.2. Governing equations

This section presents the central equations that govern the simulation model from the stock and flow model. The stock and flow model is not included in this paper due its size and complexity. Unlike the description of the causal-loop diagram presented in Section 4.1, this description presents further details of the rates and stocks that are critical to the functioning of the model. Thus, a direct correspondence between each component of the causal-loop diagram to each equation presented here is not applicable as these equations present further model details. A brief description of the main stock and flow that provides further modeling details follows.

The *Change in the Pre-intervention Population* over time is defined by $dPP/dt = \lambda dPP/dt = \lambda$, where λ is the *Net Population Change Pre-intervention Rate*. λ is given by the relationship between the *Effect of Longevity on Net Birth Rate*, *ELBRP*, the *Effective Survival Rate Pre-intervention*, *ESRP*, the ratio of *Initial Population* to the *Base Population*, *IP*/*BP*, and the *Change of Total Population Pre-intervention* over time, $PP(t)$ as shown by (1):

$$\lambda = ELBRP \times ESRP \times IP/BP \times PP(t) \tag{1}$$

Likewise, the *Change in the Population Post-intervention* over time is defined by $dPOP/dt = \alpha$; similar to λ, the *Net Population Change Post-intervention Rate*, α, is defined by the relationship between the *Effect of Longevity on Net Birth Rate Post-intervention*, *ELBRPO*, the *Effective Survival Rate Post-intervention*, *ESRPO*, the ratio of *IP*/*BP*, and the *Change of Total Population Post-intervention* over time, $POP(t)$ (2):

$$\alpha = ELBRPO \times ESRPO \times IP/BP \times POP(t) \tag{2}$$

A pre- and post-intervention per capita healthcare utilization value is assumed to estimate the total patient visits. For example, the portion of a chronic disease population that is not well managed (e.g., pre-intervention) generates a certain level of per capita healthcare utilization (e.g., 3.5 visits per year). Conversely, the same portion of the population engaged in a chronic disease management (e.g., post-intervention) will produce relatively less per capita utilization (e.g., 1.5 visits per year).[71]

To gain knowledge of the impact of an intervention, projections of the adopted metric must be generated over time.[72] The most effective course of action, and therefore the most competent treatment, are determined by the intervention strategy that displays the lowest per dollar QALY.[73] This traditional *Cost Effectiveness* measurement is defined by the ratio of the difference between the cost of the two intervention situations and the difference between the QALY related to each treatment. The *Cost Effectiveness*, ω, is given by the following equation:

$$\omega = \frac{(Costs\ post\ intervention - Costs\ pre\ intervention)}{Additional\ QALY\ gained} \tag{3}$$

The target patient population uses the healthcare system prior to and after the deployment of theoretical intervention. The model determines *Healthcare Spending* simultaneously for both population flows and calculates the prospective *Cost Saving* by computing the difference between the two associated healthcare expenditures. The *Population Pre-intervention* affects the *Pre-intervention Utilization* that determines the *Healthcare Spending Pre-intervention*. The *Longevity Pre-* and *Post-intervention* affect the *QALY Pre-* and *Post-intervention*, respectively. Both the population flows affect also the *Total Utilization Pre-* and *Post-intervention*, which in turn determines the *Healthcare Spending*.

The *Intervention Budget* stock represents the change in the intervention budget deployment over time and is defined by $dB/dt = \nu - \kappa$, where ν represents the intervention investment rate in which money from scheduled intervention deployment is invested and accumulated in the budget stock, while κ represents the budget depletion rate. ν is related to the *Average Cost Effectiveness* that influences the pace at which intervention investments flow into the budget during the deployment period. This model presupposes that intervention will be implemented in the first years of the evaluative period. The *Expenses Rates* is given by (4), where *CIPP* is the *Cost of Intervention per Patient*, *EFT*, the *Effective Fraction of Population Target*, *Population*, $POP(t)$, and the *Change in the budget over time*, $B(t)$:

$$\theta = IVR \times CIPP \times EFT \times POP(t) \times B(t) \tag{4}$$

The *Actual Cost of Care Post-intervention*, *ACPI*, is defined by (5) and is related to the *Cost of Care per Visit Post-intervention*, *CCVPostI*, the *Effective Outcome of Targeting*, *EOT*, the *Average Visits*, *AV*, and *the Cost of Care per Visit Pre-intervention, CCVPreI*, as follows:

$$\begin{aligned} ACPI = {} & (CCVPostI \times EOT \times AV) \\ & + (CCVPreI \times AV \times (1 - EOT)) \end{aligned} \tag{5}$$

Both pre- and post-intervention healthcare expenditures determine the level of savings, as denoted by *Savings in Healthcare Costs*. The change in the *Savings* over time is provided by $dS/dt = \rho - \psi dS/dt = \rho - \psi$, where ρ is the *Savings Credit Rate* while ψ is the *Savings Depletion Rate*. ρ is defined by difference between the *Pre-intervention Cost of Care per Intervention*, and the *Actual Cost of Care Post-intervention*, which control the accumulation of *Savings*. ψ is determined by the *Average Budget Expenses*, $\psi = E(t)$, and varies over time. It represents the effects of intervention budget reductions that are smoothed out over time to capture delay effects that stem from the time differentials between spending money for the intervention deployment and the effects on savings.[61]

In the savings target scenario, the goal-seeking structure adjusts over time until the system stabilizes when the savings pressure from the target is reduced to near zero. The *Savings Pressure*, *SP*, is defined by the difference between the *Target Savings*, *TS*, and the *Post-Intervention Actual Savings*, *AS*. The presence of this difference forces the model to adjust the *Cost of Care Pressure*, *CCP*, and the *Cost of Intervention Pressure*, *CIP*. When the difference is large, the pressure for adjustments is proportionally large, and therefore the cost adjustments of that intervention are large.

The magnitude of influence that the *SP* has on both the *CCP* and *CIP* can be characterized as Equations (6) and (7). This influence is driven by the elasticity associated with the each of these variables. By definition, the elasticity determines the degree of change in the parameter in response to a unit change in the effectors,[74] which in this case corresponds to *SP*. The system responds to these pressures by adjusting costs and reducing the gap created between the actual and target savings until this difference is negligible, meaning the savings pressure relaxes:[61]

$$\begin{aligned} &Cost\ of\ Care\ Pressure = \\ &Cost\ of\ Care\ Elasticity \times Savings\ Pressure \end{aligned} \tag{6}$$

$$\begin{aligned} &Cost\ of\ Intervention\ Pressure = \\ &Cost\ of\ Intervention\ Elasticity \times Savings\ Pressure \end{aligned} \tag{7}$$

The *Actual Cost of Intervention per Patient*, *ACIPP*, and the *Actual Cost of Care per Patient, ACCPP*, are influenced by the *CIP* and the *CCP*, respectively. The *Total Cost of Intervention*, *TCI*, is determined by the *Cost of Intervention per Patient*, *CIPP*, the *Total Patient Population*, *TPP*, and the *Fraction of the Patient Population Targeted* that is aimed for the intervention, *FPPT*.

The *ACIPP* also includes an amplification cost component that seeks to reflect increases in cost care per patient over time.[13,38] This increase further erodes the potential savings from the implementation of interventions. This erosion leads to a decrease in *Cost Effectiveness*.

Decreases in *Cost Effectiveness* reflect major cost reductions required to meet target savings. Since fewer costs are used to accomplish the same health benefits, *Cost Effectiveness* metrics reflect this attrition. However, efficiencies in the healthcare system are indirectly accomplished by reductions in costs via exerting pressures on their structural components based on allowable elasticity, as mentioned in the introduction of Section 4.

Decreases in savings lead to increases in saving pressure that constantly seek equilibrium given the target savings by adjusting cost components and continuously evaluating resulting outcomes. This path-adjustment cyclical process is repeated through the life of the entire run until the execution ends.

5. Simulation and results

Prior to executing the simulation, initial parameter values must be set. Different sets of initial values characterize dissimilar theoretical scenarios. These results are believed to assist in developing managerial insights on the cost effectiveness of implementing a set of interventions and how these costs may change over time. Furthermore, these outcomes provide guidance in cost corrections that may be necessary to obtain target savings. As indicated before, the objective of this framework is to characterize and observe the system behavior that embeds a goal-seeking structure under certain conditions. Thus, independently of the values employed, the capability to set an evaluating structure capable of mimicking the dynamics of cost adjustment endeavors required to accomplish a given saving target is sought in this article. A combination of real-world and theoretical values is assumed while focusing on the agreement of the generated behavior.

Each scenario may be simulated by producing a different tendency. Table 2 exhibits selected values employed to initialize the simulation. The table indicates two sets of values that include (A) for global parameters that contain values assumed for the entire simulation and (B) parameters that are exclusively associated with the intervention. For example, consider the *Cost of care elasticity* that is assumed to be 0.1, which reflects a theoretical buffer that allows decision-makers to optimize their resources and operations. Conversely, the *Cost of intervention elasticity* is assumed to be 0.01, which theoretically reflects the cost rigidity associated to applying an intervention. Perhaps, the costs of calling a patient to follow up and remind him or her to take medication have a lower degree of cost flexibility and may be marginally affected by its elasticity.

The health status pre-intervention is assumed to be 2 on a 1–5 scale and the pre-intervention per capita

Table 2. Initial values.

Constant	Value	Unit	Description/source (citation)
A. Global parameters			
Cost of care elasticity	0.1	Dollar/Year	Capacity of the cost of care to change.
Cost of intervention elasticity	0.01	Dollar/Year	Capacity of cost of intervention to change.
Cost of care per visit pre-intervention	146	Monetary Unit/Visit	Cost per visit per patient, before the application of the intervention.[75]
Initial population	100,236,820	Person	Total population in the Southern area of the US.[76]
Intervention visit rate	3.7	Visit/(Person*Year)	Visit rate required by the intervention for patients.[77]
Min initial targeting	0.5	Dmnl	Percentage of people suffering from any type of chronic condition.[78]
Pre-intervention per capita utilization	3.41	Visit/(Year*Person)	Visit rate pre-intervention for the Southern region.[79]
Quality of life pre-/post-intervention	0.48/0.52	Dmnl	Improvement of health with the application of the intervention, for example, Mishel et al.[80]
Target savings	55,000	Monetary Unit/Year	Total amount of money to be saved due to the application of the intervention, e.g., 14,000–69,000.[81]
B. Intervention parameters			
Budget	3,853,305	Monetary Unit	Initial budget allocated for the application of the intervention. It depends on the initial cost of the intervention[76] and the total number of visits.[82]
Cost of intervention elasticity	0.01	Dollar/Year	Capacity of cost of intervention to change.
Effectiveness rating intervention	0.5	Dimensionless (Dmnl)	Percentage of the successful intervention on targeted patients.[83]
Increase in longevity post-intervention factor	3.6	Year	Healthy days/years gained in pre-intervention.[83]
Initial estimated cost of intervention (average value)	17.5	Monetary Unit/Visit	Cost of intervention. Money paid for disease management intervention.[84]
Initial estimated cost post intervention (average value)	132	Monetary Unit/Visit	Cost of treatment post-intervention that may be absorbed by healthcare institution and/or paid by patient.[75]
Intervention visit rate	3.7	Visit/(Person*Year)	Visit rate required by the intervention for patients.[77]
Post-intervention per capita utilization	2	Visit/(Year*Person)	Prospective visit rate post-intervention for the Southern region.
Quality of life pre-/post-intervention	0.48/0.52	Dmnl	Improvement of health with the application of the intervention, for example, Mishel et al.[80]
Threshold cost effectiveness	139	Monetary Unit/Year	Limit/least benefit on yearly basis for an intervention to be labeled as cost effective.[84]

utilization 3.41 visits per year, as pointed out by the literature in the target population. This has been modeled using stochastic function, which is consistent with the widely available literature and adds more realism to the model. The uncertainty factor has been embedded in per capita utilization through a random function that reflects some unexplainable randomness. Parameters such as the effectiveness of the intervention, the initial estimated cost of intervention, and cost of care or the effect of intervention on the per capita visits rate are assumed to be stochastic.

The first scenario considers the model performance when an intervention has been implemented but target savings are absent. The second scenario considers the situation in which a decision-maker projects implementing an intervention, and simultaneously, sets a target saving to accomplish. As a result, the main difference between scenarios is that the target savings in the first scenario are zero while the second scenario considers the saving target as the goal.

The scenario analysis examines the impacted cost structures when the goal-seeking mechanism is employed versus the situation in which this mechanism is not employed in the presence of an intervention deployment. The simulation model is executed under two particular scenarios for a period of 50 years. The rationale is to observe how the relevant system variables perform under ‘Intervention Deployment and Target savings is zero’ versus ‘Intervention Deployment and Target savings is different than zero.’ Vensim from Ventana Systems Inc. was utilized to execute this simulation. The system behavior is described below.

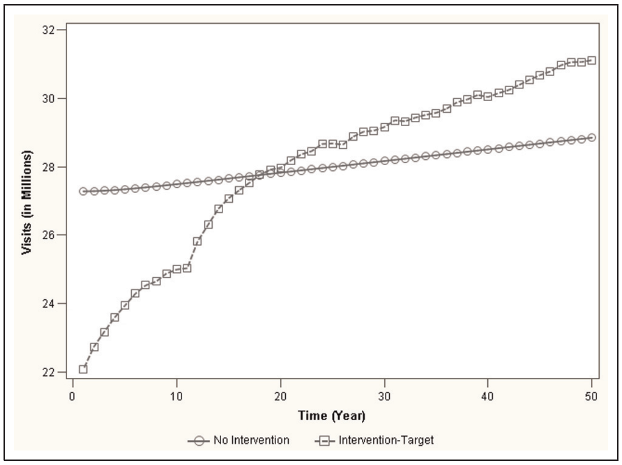

Figure 2. Patient visits.

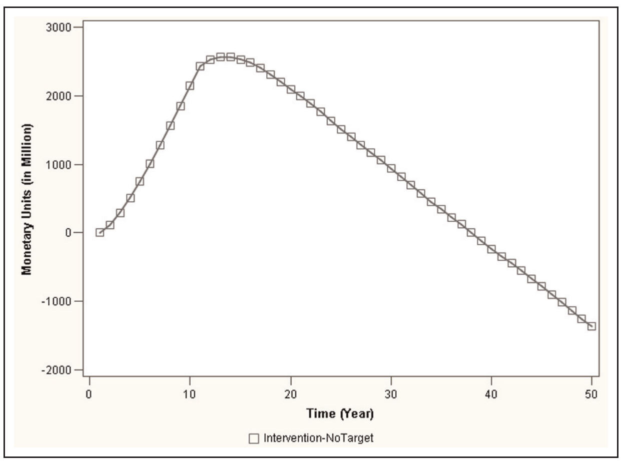

Figure 3. Net savings intervention zero-saving target.

5.1. Scenario 1: Intervention Deployment and Target savings is zero

The purpose of this scenario is to observe the behavior of key system elements under the intervention scenario when target savings are absent. Once again, in this scenario, the goal-seeking structure that strives to obtain a pre-determined level of savings is not employed. Figure 2 shows that the total visits by patients that have been exposed to the intervention initially are fewer compared to the situation in which the deployment of an intervention is not present. This behavior agrees with the expected effects of the intervention. Notice, however, in the long run, the visits rate in the 'intervention zero-saving target' setting exceeds those in the 'no intervention' setting. This increase results from the life extension obtained by the application of the intervention that produces an increase in per capita utilization at advanced age. Once again, this tendency is expected due to the increase in the likelihood

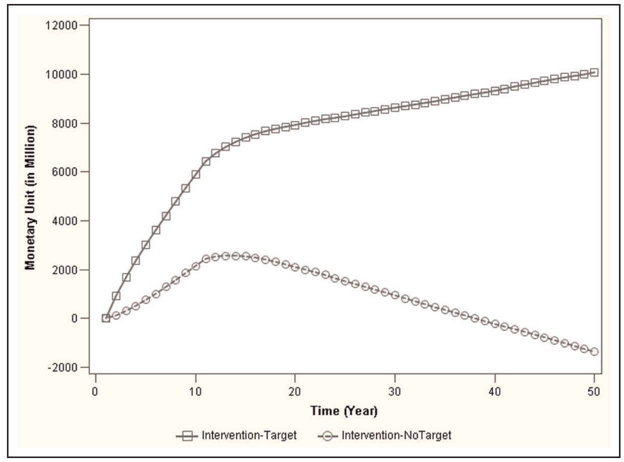

Figure 4. Net savings intervention target savings different than zero.

of developing one or more chronic conditions, as previously discussed.

The savings accumulation in the 'intervention zero-saving target' may be seen in Figure 3. Consistent with the literature, one may observe that 'intervention zero-saving target' setting produces higher net savings in the short term, since the system experiences a decrease in utilization. These savings are later eroded as the per capita utilization and the cost of utilization escalate due to aging and life extension, as well as increases in projected cost of care over time. This result suggests that the theoretical disease management intervention employed in this model may generate savings in the short run, but in the longer term, these saving are compromised.[17,18,84] This result advocates for the need of resource planning in ambulatory settings that considers projections in healthcare requirements.[15,85,86]

5.2. Scenario 2: Intervention Deployment and Target savings is different than zero

This scenario contrasts the behavior of the system for the situation in which the target savings are set to an arbitrary value versus the situation wherein this target is zero. In the first case, the target savings of the system are set at an arbitrary 40,000 monetary units (perhaps dollars), while in the second case the target savings are set to zero. Figure 4 illustrates the resulting net savings from both cases. When the target is set at 40,000 monetary units, the goal-seeking structure adjusts the cost of care and the cost of post-intervention components of the model to produce the higher net savings. Notice that initially both cases report modest levels of savings. When the target savings is different than zero, the behavior of the system suggests that the target savings can be accomplished. However, to

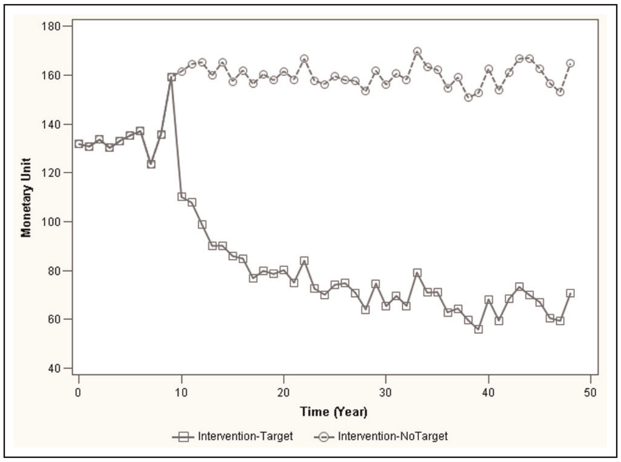

Figure 5. Cost of healthcare per visit.

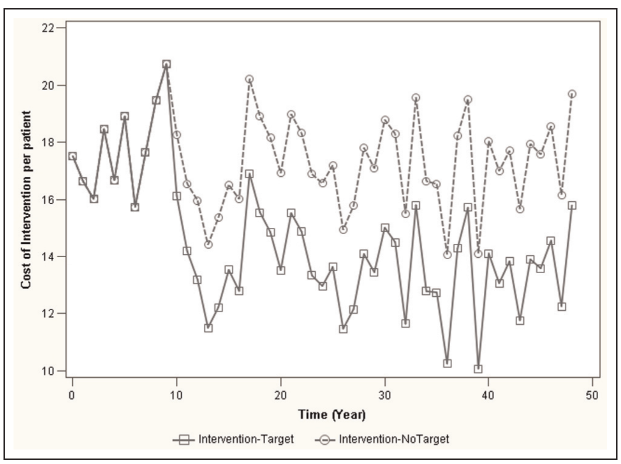

Figure 6. Cost of intervention per patient per unit time.

produce these savings a significant adjustment in the cost structure may be required.

Figure 5 exhibits the extent of the adjustment required in cost of care per patient to accomplish the target savings. These results suggest that to accomplish such savings, the downward adjustment of the cost structure requires major efforts. The required reductions in cost of care per patient to obtain the target savings can be accomplished by streamlining the processes involved in the care of patient that manage their chronic condition (e.g., following up care via technological devices), as previously discussed in Section 2. The cost reduction is not as severe in case of the cost of intervention per patient, as observed in Figure 6. This is caused by the limited effects of the elasticity associated with the cost of intervention, as assumed in this paper. In general, the cost of intervention per se is found to be significantly lower than the elements associated with the cost of care, as discussed in Section 4. As a result, the net savings obtained from reducing the cost of intervention are far less than the net saving that can be obtained by reducing the cost of care. This is reflected in the model by setting the elasticity of the intervention to be far lower than the elasticity of the cost of care.

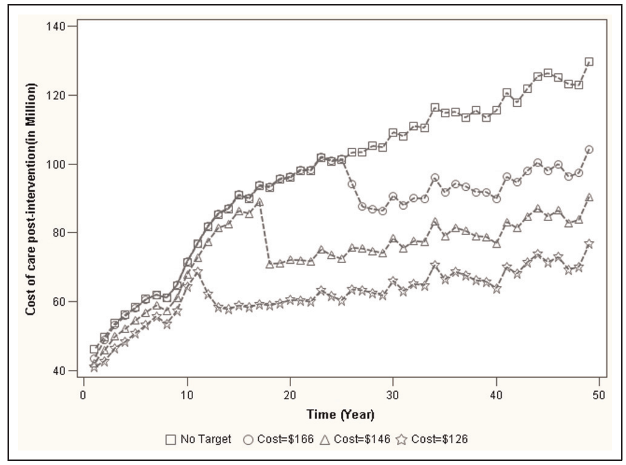

Figure 7. Cost of care post intervention.

This scenario assists in understanding the consequences that the healthcare system has to face if the target savings have to be achieved. In a more practical sense, this scenario helps decision-makers in identifying the magnitude of cost efficiency that has to be brought about in their system resulting from the intervention, if the target savings are to be realized. The information generated by the model can be employed to gain knowledge to plan and engage cost improvement programs that assist in enhancing the ambulatory cost structures, as indicated in Section 2. In this sense, public health officials, for example, may be able to explore realistic intervention alternatives that allow not only increasing health status of the target population, but also pursuing monetary savings that may require further systematic changes in healthcare delivery endeavors.

5.3. Sensitivity analysis

In this paper, the *Cost per visit per patient* is selected as an independent variable while *Cost of care per visit post-intervention*, *Actual cost of care post-intervention*, and *Cost of intervention per patient* in the presence/absence of target savings are selected as dependent variables. Furthermore, three levels of *Cost per visit per patient* are considered: US$126, US$146, and US$166. Figures 7–9 display the results obtained from conducting the sensitivity analysis to analyze the effects of changes in the *Cost per visit per patient* levels. Slight fluctuations in the performance of each cost behavior may be observed due to the introduction of a stochastic component. As indicated, these distribution functions represent the uncertainties in

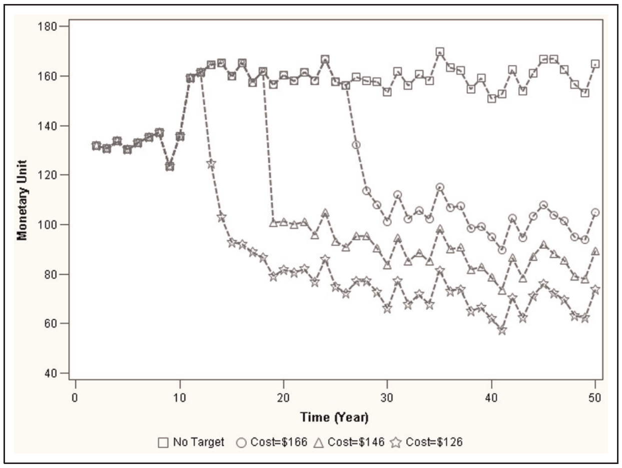

Figure 8. Cost of healthcare per visit.

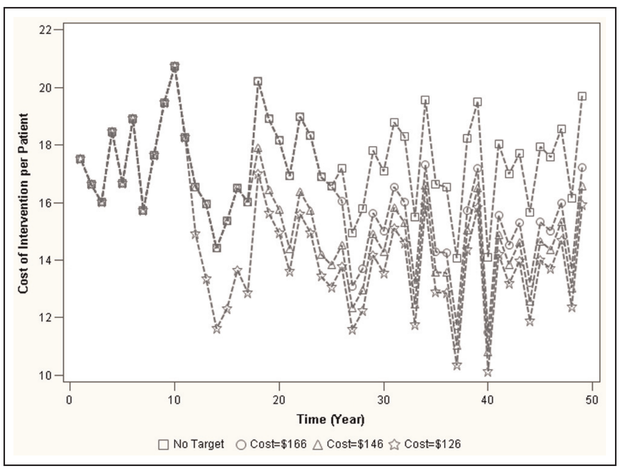

Figure 9. Cost of intervention per patient per unit time.

intervention costs.[87] Based on the behavior of each curve, two observations may be noted.

1. The cost curves whose targets are absent continue to grow over time while the ones whose targets are set display a slight initial decline and leveling that departs at different times and vary per *Cost per visit per patient* level. In the *Cost of care per visit post-intervention* chart, this decline is more pronounced. This decreasing and leveling is explained by the presence of the saving target and the action of the goal-seeking structure and the negative feedback loop acting in the model as the time progresses. The initial decline represents early cost adjustments necessary to reach the target saving. As explained previously, savings are computed as the difference between the costs pre- and post-intervention. Thus, when this difference becomes substantial while departing from the savings target, cost post-intervention adjustments are adjusted considering their associated elasticity. These adjustments seek to stabilize the actual savings as such that targets are maintained. In addition, the effects of cost amplifications experienced over time influence the cost adjustment required to obtain the target savings. These cost amplification effects increase the cost-related effort required to accomplish the established saving goals. Clearly, the more substantial and significant is the amplification factor, the more pronounced the required cost adjustments will be.
2. Each curve departs from the positive trend of growth as the target savings are accomplished. When the cost level increases from US$126 to US$146, and from US$146 to US$166, departures from their increasing tendency initiate as each tendency reaches the target savings. These timing differences are explained by the effects produced by the accumulated savings of each curve over time. A substantial difference creates a considerable gap between the actual and the target savings. The more substantial the difference between actual and target savings is, the faster the cost adjustment occurs, and consequently, the more significant the required budgetary adjustments endeavors will be.

6. Summary and managerial implications

Chronic diseases in the US constitute a sizable portion of healthcare expenditures and are projected to increase along with the aging population. PCMH is a well-known approach for continuity care that promotes disease management for mitigating some of the negative effects stemming from chronic disease. Although the appropriateness of deploying disease management interventions is widely recognized, the cost-saving potential, or at least the cost-neutrality of such interventions, is debatable.

Cost evaluations of disease management interventions are convoluted by a number of uncertainties in estimating the actual cost of delivering the intervention, the impact of intervention on the actual utilization of the system, and the overall cost to the healthcare system in the long term. Although inconclusive, the literature does suggest that certain disease management interventions can be cost saving in the short term. However, the cost-saving potential over the long term appears less favorable. Longer term cost-saving analyses based on Markov models indicate that, although disease management interventions are likely to be cost effective, they are unlikely to be cost saving in the long term.

This paper presents a system dynamics simulation model that provides a mechanism to analyze the health and monetary impact of deployments of interventions. Furthermore, it provides a tool to evaluate cost adjustments required to achieve specific savings aims. The model suggested in this paper presents a synthetic representation that reflects the dynamics of the real-world system and helps in analyzing various cost issues in the implementation of chronic disease management programs. This model embeds a goal-seeking mechanism to explore the effects of target savings on the main cost component structures and allows quantifying cost-adjustment efforts to realize these savings. The applicability of this model is demonstrated using two scenarios in which the presence and absence of target savings is assessed.

The analyses of the scenarios indicate that the application of interventions is likely to result in a decrease in utilization and an increase in savings only in the short term. Savings and utilization gains are eroded in the longer term since selected interventions lead to life extension that results in increasing prospective ambulatory utilizations stemming from increasing opportunities for the development of additional or multiple chronic diseases in an aging population. As some interventions extend individuals' longevity, the probabilities of ambulatory visits increase, in particular in elderly populations whose natural health is declining and major ambulatory utilization is expected. Such a scenario analysis is of value to stakeholders, since anticipation for planning for resources that participate in healthcare delivery is critical for matching the supply with the demand. From the operational perspective, this matching is essential to maintain optimal customer satisfaction and improve opportunities to maximize revenues. From the healthcare point of view, timely matching of available resources and patient needs increases healthcare access, which reduces population health disparities.

This study involved several limitations. Although most values employed in the simulation are actual values, the application of the evaluating framework does not seek to shed light on the effects of particular populations or interventions on healthcare systems. Generalization or the development of a case study was not a major purpose of this study. As a countless number of simulation studies can be found in the Operational Research literature, the focus of this paper is on providing a mechanism that may assist decision-makers in quantifying their managerial endeavors. In particular, the aim of this paper was to illustrate the use of goal-seeking structures to determine cost-adjustment efforts in the presence of a chronic disease management intervention.

Some of the mathematical expressions described in this paper have been simplified for demonstration purposes. Elasticity expressions, for example, have been assumed to be constant, while some research streams claim that the elasticity may present an exponential behavior based on development of underlying theories. Studies are underway to mathematically customize these expressions, and hence, to develop a model that contributes to the healthcare management of a particular community.

This study is significant for several reasons. Firstly, this research extends the relatively limited literature on the application of system dynamics to model critical components of the ambulatory healthcare system and its interaction with the application of chronic disease management interventions on population groups. It is asserted that decision-makers have to consider a large number of factors and interdependencies that are critical for the performance and sustainability of the healthcare system. A system dynamics approach offers a logical and intuitive modeling and simulation process that captures key complexities.

Secondly, the simulation framework used to develop the model presented in this paper provides an alternative estimation of the ambulatory demand method that explicitly considers interdependencies and feedback loops related to enhancements in population health. These enhancements stem from the application of successful interventions that decrease mortality rates in certain population groups and prospectively increase utilization rates caused by natural health decline in the elderly. Identifying the best possible balance among cost, responsiveness, and quality care, considering an evolving demand affected by successful interventions, requires tools that are capable of mimicking the reality of the system. Thus, healthcare managers may explore tradeoffs among proposed solutions.

Next, an understanding of the cost adjustments required to accomplish certain savings is central to the planning for the supply of healthcare personnel that will potentially face increases in the demand for ambulatory health services. Employing a modeling approach rooted in recognizing the evolving behavior of the demand and that is able to connect ambulatory utilization and health/cost impacts of interventions on population groups makes possible a more holistic understanding of the regional healthcare system. Thus, the model enables an understanding of the forces that create the mismatch between the supply and demand while providing opportunities to investigate and address this mismatch as well as health disparities.

Lastly, the suggested characterization holds the possibility to extend a further investigation of the dynamic interactions of particular interventions and specific population groups. Thus, it facilitates a better understanding of how a combination of potential interventions affects the supply and the demand, and how budget cuts and or saving targets may impact the endeavors required to accomplish the same health effects on population groups. In addition, the explicit analysis of these interventions can be used as input for sensitivity and elasticity of each intervention relative to both the patient population and the resources used to the deliver healthcare services.

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